Optimizing Game Live Service for Mobile Free-to-Play Games

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***Abstract*—In this paper, we propose a method for optimizing the game live service. Especially, we focus on improving user retention. Firstly, we define player churn in the game and extract features that contain the properties of the player churn from the game logs. And then we evaluate the importance of features using random forest in classification. Finally, we build association matrix between features and suggest a reward method for in-game events according to the relative importance of features and the interrelationships between features. Results of applying to the game in service show that the proposed scheme is enough to improve user retention.**

***Index Terms*—game analytics, churn, free-to-play, feature importances, association matrix, game live service.**

I. Introduction

Recently, mobile game industry has been shifted to Free-to-Play (F2P) game model. F2P games can be played for free, but optionally players can purchase cash items in the game. In F2P games, most game players do not spend money on In-App Purchases (IAPs). Therefore, the key challenge in F2P games is to predict player purchases in the game. As User Acquisition Cost (UAC) is high and rising in mobile games, retaining players in games has also become important issue. In order to keep User Retention Rate (URR), there is a need to determine players that will leave a game. This type of prediction is called *churn prediction*. Player churn is closely related to URR and player loyalty [1].

In recent years, various churn prediction modeling schemes have been proposed for mobile F2P games. In [2], Hadiji et al. attempted to formalize the concept of 'churn' and predict player churn under real-life condition. Runge et al. [3] tried to quantitatively define high-value player segment and predict the churn as a binary classification problem. Tamassia et al. [4] proposed a churn prediction model for the game based on hidden Markov models (HMMs), chosen due to the time-series nature of the data.

In this study, we proposed methods for optimizing the game live service that prevent player churn. It is the first time churn prediction has been applied to the game live service. Firstly, we extract player behavioral features which effectively represent player churn, and then define churn prediction models. Next, we evaluate the importance of features using random forest in classification. Finally, we build association matrix between features and suggest a reward method for in-game events according the relative importance of features and the interrelationships between features.

TABLE I
Features on Crazy Dragon

Feature Types	Features
Activity	Number of Days Inter-Login Day Distribution Event Logs per a Day Amount of Sword on the Last Logout Day Daily Sword Distribution Character Level on the Last Logout Day Daily Level Distribution
Purchase	Number of Purchases
Transaction	Amount of Gold on the Last Logout Day Amount of Ruby on the Last Logout Day Daily Gold Distribution Daily Ruby Distribution Number of Times Consuming Ruby
Sociality	Amount of Heart on the Last Logout Day Daily Heart Distribution Number of Times Attending Guild

II. Proposed Method

A. Feature Importance Calculation

In order to conduct experiments, we choose Crazy Dragon developed by Mgame. Crazy Dragon is a mobile F2P Roll-Playing Game (RPG) published on multiple platforms. In this paper, we devide player behavioral features that represent player churn into several categories, as shown in TABLE I.

In general, the number of churners in the mobile game has quite a large proportion compared to non-churners. The imbalance between churners and non-churners results in the issue of minority class that is not modeled properly. In order to solve the problem of imbalanced dataset, we use synthetic minority over-sampling technique (SMOTE) which is proposed by Chawla et. al [5].

In this paper, we define a churn prediction model that contains a full cycle of one week, as shown in Fig. 1. Firstly, we sample all players that have signed in more than once between $-7d$ and 0 because all players that have been already churners should be excluded. And then we label 'churn' that will not play the game between 0 and $7d$. Finally, we train random forest on the labeled dataset of the player behavioral features between $-14d$ and 0. Using random forest, we measure the relative importance of each feature in classification process.

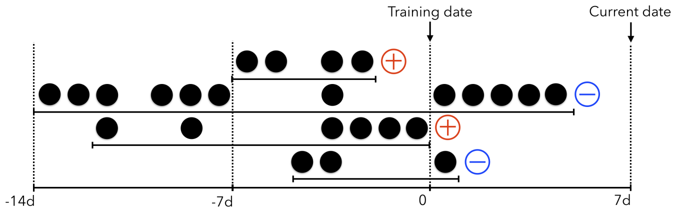

Fig. 1. Churn Definition (●: activity, ⊕: churn, ⊖: no churn)

TABLE II
RESULTS OF CALCULATING THE REWARD IMPORTANCES

Rewards	Features	Importances
Ruby	Amount of Ruby on the Last Logout Day Daily Ruby Distribution	0.2782
Gold	Amount of Gold on the Last Logout Day Daily Gold Distribution	0.1356
Sword	Amount of Sword on the Last Logout Day Daily Sword Distribution	0.2589
XP	Character Level on the Last Logout Day Daily Level Distribution	0.0720

B. Reward Importance Calculation

Using Pearson correlation coefficient (PCC) [6], we compute the association matrix between player behavior features and reward features. PCC is a measure of the linear correlation between two variables. It has a value between $+1$ and -1, where 1 is total positive linear correlation, 0 is no linear correlation, and -1 is total negative linear correlation. And then in order to calculate reward importances, we use average of the absolute values of correlation coefficients between reward features and important behavior features as follows: $r_k = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|c_{ij}|$ $(k = 1, \cdots, L)$, where L is the number of rewards, M is the number of reward features for each reward, N is the number of the most important features, and c_{ij} is the correlation coefficients between M reward features and N most important features.

Finally, we decide the amount of each reward according to the corresponding reward importance. It is reasonable because the amounts of rewards are highly related to behavior features that have a lot of influence on the user retention.

III. EXPERIMENTAL RESULTS

In the experiment, we applied the proposed method for optimizing the live service on Crazy Dragon. First, we adopted random forest to build the churn prediction model. Random forest algorithm was implemented by Python Scikit-Learn library (version 0.17.1). Also, we used SMOTE to tackle a skewed distribution of player churn. In order to implement SMOTE, we applied Python Imbalanced-Learn Library (version 0.2) that is fully compatible with Scikit-Learn.

Using random forest in classification, we observed the relative feature importances about $1,500$ players. And then we calculated the reward importances as described in Section II-B. In the experiment, we used the correlation coefficients between the reward features and the top 3 most important behavior features. TABLE II shows the results of calculating the reward importances. As it can be seen in TABLE II, the most important reward is 'Ruby'. Therefore, we focused on Ruby' reward for the improving user retention.

Finally, we applied the reward importances to the live service on Crazy Dragon. According the reward importances in TABLE II, we determined the amount of each reward and served as a reward to players through the in-game event. And then we calculated percentage change in average URR after 14 days since players received the rewards. We define this type of the URR as $D + 14$ URR. Through applying the above live service on Crazy Dragon, we had an improvement 5.19% in average $D + 14$ URR comparing to before the in-game event. In addition, there was an increase 2.52% in the number of logins that is one of user retention related logs during in-game event. On the other hand, giving the players more free rewards to keep them playing longer caused a decrease 5.4% in the number of their IAPs.

IV. CONCLUSION

In this paper, we proposed a method for optimizing the live service on mobile F2P games. In order to calculate the reward importances, we use interrelationships between the reward features and the most important behavior features. To evaluate the performance of the proposed method, we chose a live mobile F2P RPG game and applied the reward importances to the live service. Experimental results show that the proposed method has an improvement enough to optimize the live service for the user retention. In future work, we will extend the proposed method to improve player purchases and engagement. In addition, we will exploit various in-game components such as environmental and psychological features.

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